

In earlier work, we proposed a super-resolution (SR) method that required the availability of two low resolution (LR) sequences corresponding to two different sampling rates, where images from one sequence were used as a basis to represent the polyphase components (PPCs) of the high resolution (HR) image, while the other LR sequences provided the reference LR image (to be super-resolved). The (simple) algorithm implemented by Salem and Yagle is only applicable when the scene is static. In this paper, we recast our approach to SR as a two-stage example-based algorithm to process dynamic scenes. We employ feature selection to create, from the LR frames, local LR dictionaries to represent PPCs of HR patches. To enforce sparsity, we implement Gaussian generative models as an efficient alternative to L1-norm minimization. Estimation errors are further reduced using what we refer to as the anchors, which are based on the relationship between PPCs corresponding to different sampling rates. In the second stage, we revert to simple single frame SR (applied to each frame), using HR dictionaries extracted from the super-resolved sequence of the previous stage. The second stage is thus a reiteration of the sparsity coding scheme, using only one LR sequence, and without involving PPCs. The ability of the modified algorithm to super-resolve challenging LR sequences reintroduces sampling rate diversity as a prerequisite of robust multiframe SR.